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Improved chaos genetic algorithm based state of charge determination for lithium batteries in electric vehicles

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ABSTRACT

Lithium batteries are developed rapidly in electric vehicles, and the accurate online evaluation of available capacity for ensuring their safety and functional capabilities is challenging due to the stability of initial value, extensive computational requirements and convergence issues. This paper proposes an improved chaos genetic algorithm based method to evaluate the state of charge of batteries with low computational complexity and high initial stability. Based on a combined state space model employed to simulate battery dynamics, an improved chaos genetic algorithm based method which comprises chaos genetic algorithm, Ampere hour approach and adaptive switch mechanism is advanced to predict the available capacity. The method is validated by the experiment data collected from battery test system. Results indicate that the improved chaos genetic algorithm based method shows great performance with low computational complexity and is little influenced by the given initial value.

1. Introduction

Nowadays, $LiFePO_4$ batteries are developed rapidly in electric vehicle (EV) and hybrid electric vehicle (HEV). Compared to other lithium batteries such as $LiCoO_2$, $LiMn_2O_4$ and $LiNiO_2$, $LiFePO_4$ ones provide benefits of low cost, safety, longevity and environmental compatibility. The rate capability of $LiFePO_4$ is a critical issue for the commercialization of Lithium batteries in HV and HEV, which is an integral part of their battery management systems [1]. Accurate estimation of available capacity is important for the safety and functional capabilities of the whole system. Failure cases might bring reduced performance, operational damage and even disastrous results.

As a value incapable of being detected directly, cell SOC is usually accessed by the methods based on the characteristics of the batteries. Many different types of models have been developed for batteries, such as electrochemical model, preisach model, impedance based model and electrical circuit model (ECM). Electrochemical model is very computationally expensive so that its use for online estimator design occurs to be impractical [2]. A simplified electrochemical model with a certain cost of accuracy was presented in Ref. [3]. Reference [4] presents an adaptive discrete Preisach model and its deformation algorithm to describe the relationship between open circuit voltage (OCV) and state of charge (SOC), but the OCV cannot be measured online. ECM is extensively used for battery state estimation because of their relatively simple mathematical structure. Based on a first-order circuit with one RC network to simulated battery dynamics, reference [5] employs an adaptive gain sliding mode observer to evaluate cell SOC. Combined with experience equations, reference [6] uses a second-order circuit with two RC networks to simulate battery characteristics. Reference [7] discusses the normal equivalent circuit models with different number of RC networks to model the polarization characteristic and the dynamic behavior of the lithium-ion battery, and accesses cell SOC based on the online identification of its open-circuit voltage.

The $LiFePO_4$ battery is a nonlinear dynamic system, so is its established battery model. Typical model-based estimation algorithms [8] include Luenberger observer, sliding-mode observer and Kalman Filter. Kalman filter is a most common selection for accessing cell SOC. It operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. Literature source [9] uses discrete wavelet transform (DWM) based denoising technique for discharging and charging voltage signals, inverse DWM of the filtered detailed coefficients for signal reconstruction, and ECM-based algorithm with extend Kalman filter (EKF) for SOC estimation. It may eliminate measurement noise effectively. Reference [10] uses EKF to update the battery pack parameters by the real-time measured data and the unscented Kalman filter (UKF) to estimate the battery pack state-of-charge. Based on a multi-cell battery model, reference [11] uses a traditional EKF to evaluate cell SOC. Reference [12] adopts EKF for

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evaluation when there exists high SOC sensitivity versus cell terminal voltage. However, whether EKF or UKF [13] based methods, they rely significantly on the given initial value. Endowed a more accurate value, the predicted value would converge to the real one more quickly. Otherwise, the estimation accuracy will decline and the convergence can even be lost in some cases. Reference [14] introduces an unscented particle filter (UPF) method with a degradation method into the remaining useful life prediction of battery. Based on a combined model considering the drift current of the sensor, reference [15] adopts UPF to access cell SOC. Reference [16] proposes a stochastic model based UPF method. Particle filter (PF) methods employ random particles satisfied with specified distribution to represent cell available capacity for solving this problem but bring great amount of computation.

Newton's method is one of the most popular numerical methods to solve nonlinear equations. It is simple in form and converges quadratically. However, calculating on the Jacobian matrix and its inverse is quite time consuming, and the method may fail to converge which will result in an oscillation between points [17]. Improved Newton's methods like Broyden's method have certain advantages, such as computation amount reduction, but they still have the same disadvantage of approaching locally.

Genetic algorithm (GA) search parallel from a population of points through the bio-inspired operations of selection, crossover and mutation [18]. It has the ability to avoid being trapped in local optimal solution like traditional methods, such as Newton's method and Broyden's method. Nevertheless, GA has the weakness such as slow convergence, easy to be premature and impractical to guarantee converging to global optimization. Chaos is a common phenomenon in nature, which has many characteristics, such as initialization sensitivity, ergodicness and disciplinarians. It may come through all states with rules in itself. Reference [19] uses the logic map function to produce the chaotic initial population. Reference [20] employs the mixing of chaotic and non-chaotic individuals to represent the initial population and the logic function as a genetic operator in the crossover process to improve the rate of calculation. Chaos genetic algorithm (CGA) combines the advantages of GA's global search ability and chaos' attributes like effective ergodicity [21]. Nevertheless, the application of CGA enlarges computational complexity.

Compared to other methods, Ampere hour (AH) counting method is the basic approach followed directly by the definition of SOC and requires a small amount of computation. However, it is also sensitive to the given initial available capacity and needs regular re-calibration.

To address the existing issues in battery SOC estimation, this paper presents an improved chaos genetic algorithm (ICGA) based method, which combines the global search ability of genetic algorithm with the randomicity and ergodicity of chaos, to search the initial available capacity of batteries, while introducing the adaptive switch mechanism and AH counting approach to reduce calculation amount. It is organized as follows. This paper first employs a combined state space model to evaluate battery dynamics, such as open-circuit voltage, available capacity, polarization effect and transient response. Then an ICGA based method is used for the SOC prediction of $LiFePO_4$ batteries at different discharging and charging current. Finally results of lab tests on 18650 size cells with pulse discharging current, contrasted with different prediction methods, are presented.

2. Battery modeling

Since SOC is unable to be detected directly, a precise cell model about SOC must be established first for $LiFePO_4$ batteries.

2.1. Dual polarization (DP) model

Besides simple to understand, an effective electrical circuit model may represent the entire dynamic behavior of cell. DP model [6], as depicted in Fig. 1, is a two-order electrical circuit model. It includes three parts: open-circuit controlled voltage (V_{oc}), ohmic resistance R_o and the shaded RC parallel network which is composed of electrochemical polarization resistance (R_{pa}), electrochemical polarization capacitance (C_{pa}), concentration polarization resistance (R_{pc}) and concentration polarization capacitance (C_{pc}). DP model may characterize the transient response and polarization effect of cell, such as electrochemical and concentration polarization effect. Nevertheless, it does not describe the nonlinear relation among open-circuit voltage, charge and discharge rate current and SOC.

2.2. Experience model

Experience model usually describes cell model as

$$V(t) = V_{oc}(SOC(t)) - i(t)R_o = [K_0, K_1, K_2, K_3, K_4] \\ [1, SOC(t), 1/SOC(t), \ln(SOC(t), \ln(1 - SOC(t)))]^T - i(t)R_o \tag{1}$$

where $V(t)$is the terminal voltage and $K_i (i = 0, 1, 2, 3, 4)$ is the coefficient. The experience model gives a description between cell SOC and open circuit voltage $V_{oc}(SOC(t))$, but does not characterize the temperature, transient response and hysteresis effect of cell. So there exists certain difference between the real voltage and the output of experience model.

2.3. Combined state space model for $LiFePO_4$ batteries

Ampere Hour (AH) method usually defines SOC as the ratio of standard available capacity to the nominal capacity (*Cap*),

$$SOC(t) = SOC_0 - \frac{1}{Cap} \int_0^t \eta(i(t), T(t)) i(t) dt \tag{2}$$

where SOC_0 is the initial value, $SOC(t)$ is the cell SOC at the time t, and $\eta(i(t), T(t))$ is cell coulombic efficiency which differs with charge and discharge rate current $i(t)$ (assumed positive for discharge, negative for charge) and cell temperature $T(t)$.

Based on the established SOC definition equation, experience and DP model, a combined state space model is achieved for $LiFePO_4$ cells [6],

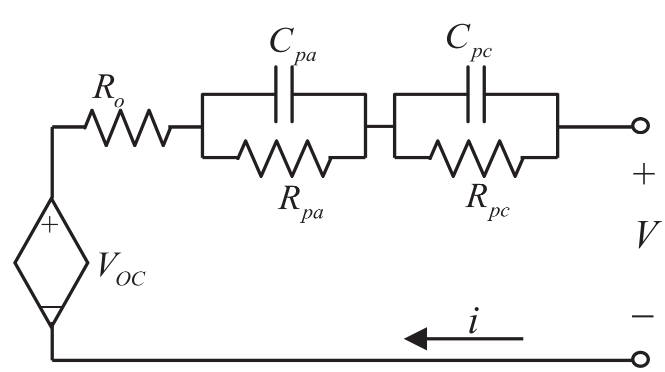

Fig. 1. Electrical circuit model for $LiFePo_4$ batteries.